

Development of neural network to detect anomalies in artery scan videos



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Project Overview

The client is a major medical equipment vendor in the US market. The company is focused on automated external defibrillators (AEDs) and ultrasound scanners distribution, as well as promoting their own services for artery scanning. The service is delivered to US-based medical institutions, and physicians in private practices.

Problem

The solution for assessing the condition of cervical arteries includes a portable scanner and a detailed interpretation of scan results provided by experienced technicians on the vendor's side. So, a physician makes an artery scan video, submits it to the vendor and receives a PDF statement that contains artery data and relevant frames where cholesterol plaques, their position and size, are shown.

Previously, specialists on scans transcription had to view the entire video recording — which is an average of five minutes long — checking the condition of the artery shot by shot to identify shots that require a doctor's attention and to determine the presence of cholesterol plaques. Measuring the thickness of the artery wall and its diameter, determining the plaques shape, size and position were also performed manually. Obviously, this routine is time-consuming and therefore expensive.

So the solution price was very high for final customers, as well as overhead expenses:

- The scanning device could be afforded only by large hospitals due to its costliness and large format;
- Scanning results had to be manually analyzed by humans, requiring time and increasing costs.

Therefore, the challenge was to optimize the hardware price tag, to migrate the current software into a more space-effective scanner, and finally, to automate the ultrasound scan reading and anomaly detection, allowing the human analyst to issue statements without a detailed video examination.

Why WaveAccess?

WaveAccess was chosen as a solution provider due to its previous experience in Healthcare IT:

- Successful Healthcare IT projects portfolio
- Acknowledged Machine Learning projects
- Microsoft Silver Partner status and Microsoft Partner Awards for a machine learning based project
- Relevant publications in specialized media
- Reliable and motivated team

Solution

The Client decided to replace large format equipment with more cost-effective portable scanners, and our first goal was to recreate the user-familiar interface and integrate it with the new device.

The second goal was to automate the scan reading. The system had to be able to detect a plaque, to calculate the intima-media thickness (IMT) which is directly related to the chance of finding a plaque, and to provide the analyst with an almost-ready statement with relevant frames.

Stage 1: Interface development and device integration

The first goal was segmented into the following sub-goals:

- Develop a service to scan video recording
- Integrate it with the new device
- Store the recorded scan videos at a file server
- Configure a doctor workstation as a web service.

At this stage, some system bugs were fixed: storing all work sessions in the same directory and structure, some UI inconveniences, difference between some measurement parameters. We moved all data into a new system: video footages patient forms were previously unorganized, and now they are conveniently structured into folders.

Fig. 1. Patient data is associated with folders of the same name, making it easier to find

The interface itself was also tweaked: Previously, the IMT had to be measured by impromptu means. Now a number of graphic libraries can be used to calculate IMT, and a custom measurement tool allows measurements at any angle.

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Fig. 2. Web interface now has a tool for instant IMT and plaque size measurement

Stage 2: Scan reading automation

The main goal here was to develop a module and to "teach" it to detect anomalies as quickly as an experienced doctor would – say, to tell a plaque from an image artifact or noise. But cholesterol plaques come in various shapes and sizes, making it difficult even for a seasoned expert to spot an anomaly. Artery measurement is also not a routine task. For challenges like these, a machine learning based module fits right in.

Training data (both videos and detailed statements) was very limited, since it had to be prepared manually by the Client's analysts, who are always under time constraints. Therefore, several algorithms were used in the module: one for finding frames to measure IMT,

Convolutional neural networks are instrumental for visual recognition in scan results according to the training data, therefore solving the task of detecting arteries position as well as potential cholesterol plaques. In this setting, two different convolutional neural networks were trained and used – for IMT measurement and for plaque detection.

Convolutional neural networks are based on mathematical operation of convolution. In terms of our goal, the network can be considered to be a map of the parent matrix over the chosen kernel, forming a certain new type. A number of kernels is used for convolution, and as the convolution progresses, the model analyzes the attributes of growing size. Then a generative network is applied to get the specific areas.

For this project we have developed a convolutional neural network that receives a part of a frame. That part of a frame is picked out by another convolutional network and it is likely to contain an artery position.

The convolution is based on a large number of mathematical kernels. As the convolution progresses, the network analyses more complex attributes. Then, a generative network is used to define the area that contains plaque. Convolution results are transferred to a fully connected neural network that decides whether a plaque is present on the frame. If the decision is positive, then the remaining result from the generative network is used to find the plaque's position.

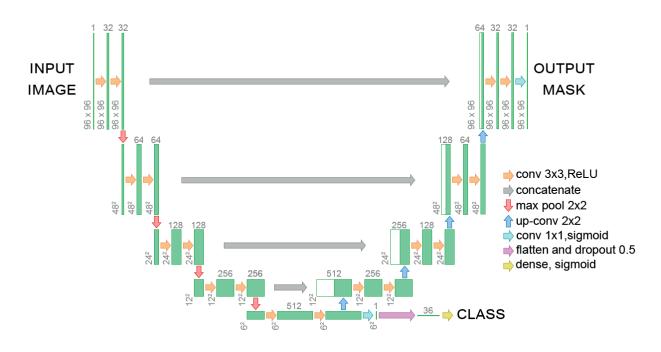


Fig. 3. Final neural network structure

The training data for plaque detection consisted of 625 frames, 208 of them (approx. 33%) contained a plaque, while others did not. Actual plaque images cropped from the original frames were placed right in the middle, creating a so-called mask.

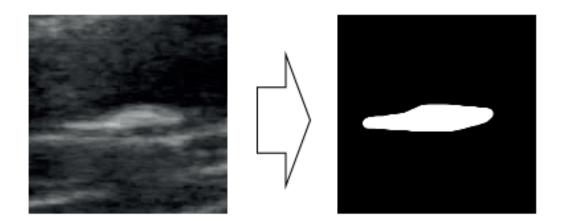


Fig. 4. Plaque image and training mask

The network that detects the artery position and the plaque search area was trained in a similar way.

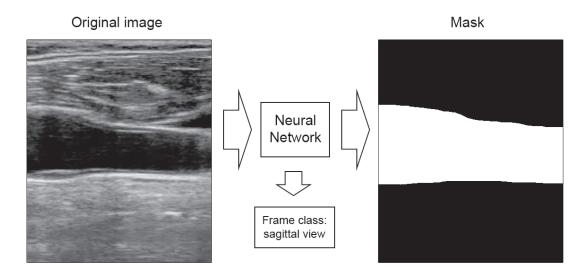


Fig. 5. Artery image and training mask

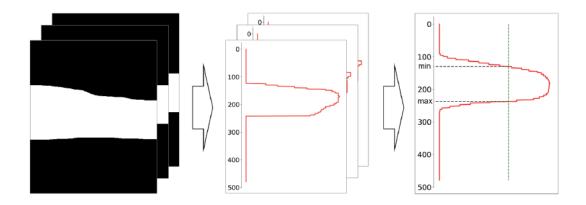


Fig. 6. An example of threshold to detect an artery

Haar cascades. Since the artery IMT is not as various as plaque size and position is, Haar cascades are convenient for artery IMT measurement. This technique comes in handy to detect the areas where artery wall thickness measurement was possible. Haar-like feature based algorithm detects the said areas using the cascade ensemble learning: it applies several successive complex classifiers to an array of images, and each classifier discards areas that appear irrelevant.

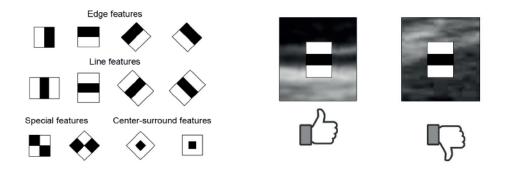


Fig. 7. Haar-like features and an example of matching and reaction

There are two types of data for training: positive (frames that are fit with artery IMT already measured) and negative (just random frames). The dataset consisted of 110 positive and 460 negative samples.

The model splits the ultrasound scan video into frames and provides the human analyst with 20 highlight frames with potential anomaly areas and 5 shots that are best positioned for artery IMT measurement.



Fig. 8. The system automatically detects the artery position and plaque search area

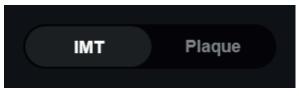


Fig. 9. The module returns frame numbers and marks positions that are best for artery IMT measurement, in validity order

After training on test data, the system was released to the Client's analysts for action learning. Before reviewing the entire video footage, the analyst would refer to the module output results. Samples of valid and invalid outputs were passed back to the developers for further training.

Difficulties

Scanner integration. One of our goals was to integrate the software with the new space-efficient scanner. But we could not have the actual scanner delivered to our office due to its fragility and price tag. We expected it to be detected as an ordinary video camera, which would allow for using regular cameras for testing. But the fact was that the stream from artery scanner is different from that of a camera, and we need to connect to the real scanner.

- So the testing was possible only via remote connection. The scanner was connected to a workstation in a different time zone, so in case of connection error we had to postpone the testing again and again.
- We also had to use the scanner's native local software. Moreover, the scanner couldn't be detected by any of the common browsers (Chrome, FF, Opera, IE, Edge).

The first problem of remote connection was successfully solved over time, but the second one turned out to be a hard nut to crack. We took a lot of effort to negotiate with the native software provider. We expected Chrome to work, but in fact we had to test all browsers available, and eventually figured that only Yandex browser was able to detect the stream. So we had to use it, fix a number of bugs and get a fully functional service.

Testing. Testing and debugging was done remotely using the customer's workstation with the installed scanner. Due to 10-hour time zone difference, we in fact had to lose the entire working day in case something went wrong with the testing machine. Nevertheless, the system availability was tested without any deadline extension.

Choosing a HIPAA-compliant hosting. Since the medical data we worked with required special protection, we had to choose and configure a secure yet affordable environment to secure the sensitive data.

| Technologies

For web interface integration:

- Java spring (data, security, integration-ftp);
- Hibernate ORM, an object-relational mapping tool for the Java programming language, distributed under the GNU Lesser General Public License;
- Flyway, a database migration tool.

The neural network architecture was designed using the Keras library with TensorFlow backend. The basic programming language used was Python. Tools used:

- TensorFlow, an open-source software library for dataflow programming by Google; tensorflow-gpu for GPU integration.
- Keras, an open source neural network library written in Python and capable of running on top of Deeplearning4j, TensorFlow, and Theano frameworks;
- Sklearn, a machine learning library for Python;
- Scikit-image, an image-processing library for machine learning in Python;
- OpenCV, a library of programming functions mainly aimed at real-time computer vision.

Algorithms used:

- Haar-like cascades, for defining the artery wall thickness;
- Convolutional neural networks, for defining the measurement area and to detect a cholesterol plaque;
- Generative neural networks, for finding specific areas to examine.

Results

The client's analysts now do not have to review the entire ultrasound scan. Together with the source scan video from a physician, they receive a set of 20 highlight frames to find a plaque and 5 clear frames to measure the artery wall thickness.

- The company has managed to keep 10 analysts and avoided staffing up. The analysts get more tasks done.
- The solution price has become more competitive due to savings on expensive human resources.
- Automatic plaque detection has reduced the chance of medical error.
- The solution price was also reduced due to web interface and free customized library to process the artery wall thickness.
- Patient data storage was optimized.

The artery wall thickness in calculated with 95% accuracy, potential plaque detection is 80% correct. Having received the frames, the analyst can use the built-in ruler tool to make measurements at different angles.

Client testimonial

"The application is fabulous and I know it is going to be a big hit with our doctors and their staffs. Congratulations to all who worked to create this outstanding result!"

- Rachel Cunningham, Chief Executive Officer



If you have a project for us, please get in touch

scientific@wave-access.com Skype: wave_access

+1 866 311 24 67

wave-access.com